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The Human Factor: Equipping Our Digital Workforce

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Current and Future State Overview

It is crucial that we recognize the role of the manufacturing worker has had in building manufacturing capabilities, a cornerstone of US competitiveness. Investment in innovative, smart manufacturing processing methods, industrial cyber-physical systems (ICPS), automation technologies, and information/operational technology (IT/OT) has advanced US manufacturing (across small, medium, and large manufacturing enterprises) connectivity, automation, and operational efficiency (Reischauer, 2018, Kim et al., 2018, Lasi et al., 2014).

As an enabler of smart manufacturing, industrial cyber-physical systems (ICPS) are critical to the success of manufacturing (Ahmed et al., 2021). In ICPS, the cyber, physical, and hybrid technologies integrate billions of objects with unique addressability, with or without human involvement. The volume of information generated in smart and connected factories is overwhelming, and worker roles must change as traditionally separate IT and OT domains converge (Gartner, 2014). Information technology covers "...[t]he entire spectrum of technologies for information processing, including software, hardware, communications technologies, and related services. IT does not include embedded technologies that do not generate data for enterprise use." Operating technology "[i]s hardware and software that detects or causes a change through the direct monitoring and/or control of physical devices, processes and events in the enterprise" (Gartner in Desai 2016). Most US manufacturers identify the primary cause of today's worker shortage as a "shifting skill set due to the introduction of new advanced technology and automation." (Giffi et al., 2018) While more than half of manufacturers surveyed in Accenture (2015) have adopted collaborative robots (cobots), artificial intelligence (AI), and other smart manufacturing technologies, many manufacturers simply do not have a capable IT/OT workforce for implementing ICPS, which limits their ability to realize the benefits (e.g., improved cost, quality, productivity, and safety).

Even though smart manufacturing technologies and ICPS advance manufacturing worker productivity, these technologies can also be responsible for exacerbating the skill gaps (WEF, 2018). This is because ICPS shift worker skill sets, from low/medium to high-skill jobs (WEF, 2018). Further, professional skills have a reported "half-life" of five years, compelling workers to change jobs every 4.5 years (WEF, 2017). This threat is magnified due to the loss of worker knowledge and expertise through retirements of the baby-boom generation (Giffi et al., 2018). Manufacturing workers are experiencing a paradigm without precedent: a pace of skills obsolescence that requires continuous learning and career agility (WEF, 2019).

To respond to the aforementioned challenges, innovations that incorporate the expertise, flexibility, and adaptability of manufacturing workers are being investigated in industry and academia in order to reach new levels of efficiency, productivity, and safety. Example innovations include collaborative robots, augmented reality, intelligent machine tools with embedded metrology, digital twinning, IoT sensors and sensor fusion, industrial AI/ML business intelligence, ultrafast 3D printing and hybrid manufacturing, smart projector interfaces, and voice directed actions (Kim et al., 2019, Wiedenmaier et al., 2003, Cahya & Giuliani, 2018, Mihelj et al., 2019, Gattullo et al., 2019, Chheda et al., 2013).

Adapting manufacturing processes to better respond to the emerging and fundamentally different manufacturing environment requires rapid interventions and continuous worker training. Modern learning technologies, when appropriately applied, can embed learning processes intrinsic to production routines. The new training and education systems should be more worker specific and promote knowledge transfer across manufacturing workers while reducing the mental resources. The dynamic character of future manufacturing jobs requires continuous learning and new and expanded skillsets (e.g., analytics and cybersecurity) that can balance business understanding, innovative thinking, and personal integrations. The current training paradigm for manufacturing does not equip workers for future manufacturing jobs or supporting ICPS environments. Future training paradigms for ICPS environment that includes collaborative robots, augmented reality, intelligent machine tools with embedded metrology, digital twinning, IoT sensors and sensor fusion, industrial AI/ML business intelligence, ultrafast 3D printing and hybrid manufacturing, smart projector interfaces, and voice directed actions, should be designed with a human worker centric approach (i.e., a human-in-the-loop focus). However, creating these training paradigms requires a fundamental understanding of how a manufacturing human worker fits within smart manufacturing or ICPS technology loop.

Executive Summary

The digital workforce of tomorrow fits within smart manufacturing and ICPS enterprises in a framework such as that shown in Figure 1. Certain industry sectors or scales (small, medium, or large manufacturers) may see slight or major changes in the organization or aspects of Figure 1 based on relevance to their unique systems. At the heart of the framework is the manufacturing worker. While the demands, requirements, and expectations of the worker have evolved due to past industrial revolutions, the worker has still retained a central role in manufacturing enterprises. Craftsmen level manufacturing, which eventually gave way to mass production and standardized work, targets the direct relationship between the worker and machines (machines are illustrated as Resistance Spot Welding, RSW, Fused Deposition Modelling – additive manufacturing, FDM, and machining), represented by the black sensory arrow that provides feedback to the worker and the black decision/ expertise arrow. Craftsmen level work emphasizes worker sensory observation of a machine operation in order to make decisions that optimize production and quality. Decisions are solely based on expertise learned by the worker and stored in working or long-term memory. Mass production and standardized work still emphasized the worker and machine interactions but reduced the necessity of the black sensory feedback and worker decisions or expertise by creating repeatable work instructions that led to high quality, repeatable part production. Advancements in sensors, computing, and computerized numerically controlled machines enabled more advanced feedback to machines, indicated by the blue arrow from the analytics control to machines [OT] in Figure 1. Feedback is determined based on basic machine sensors, blue arrows exiting the machines [OT].

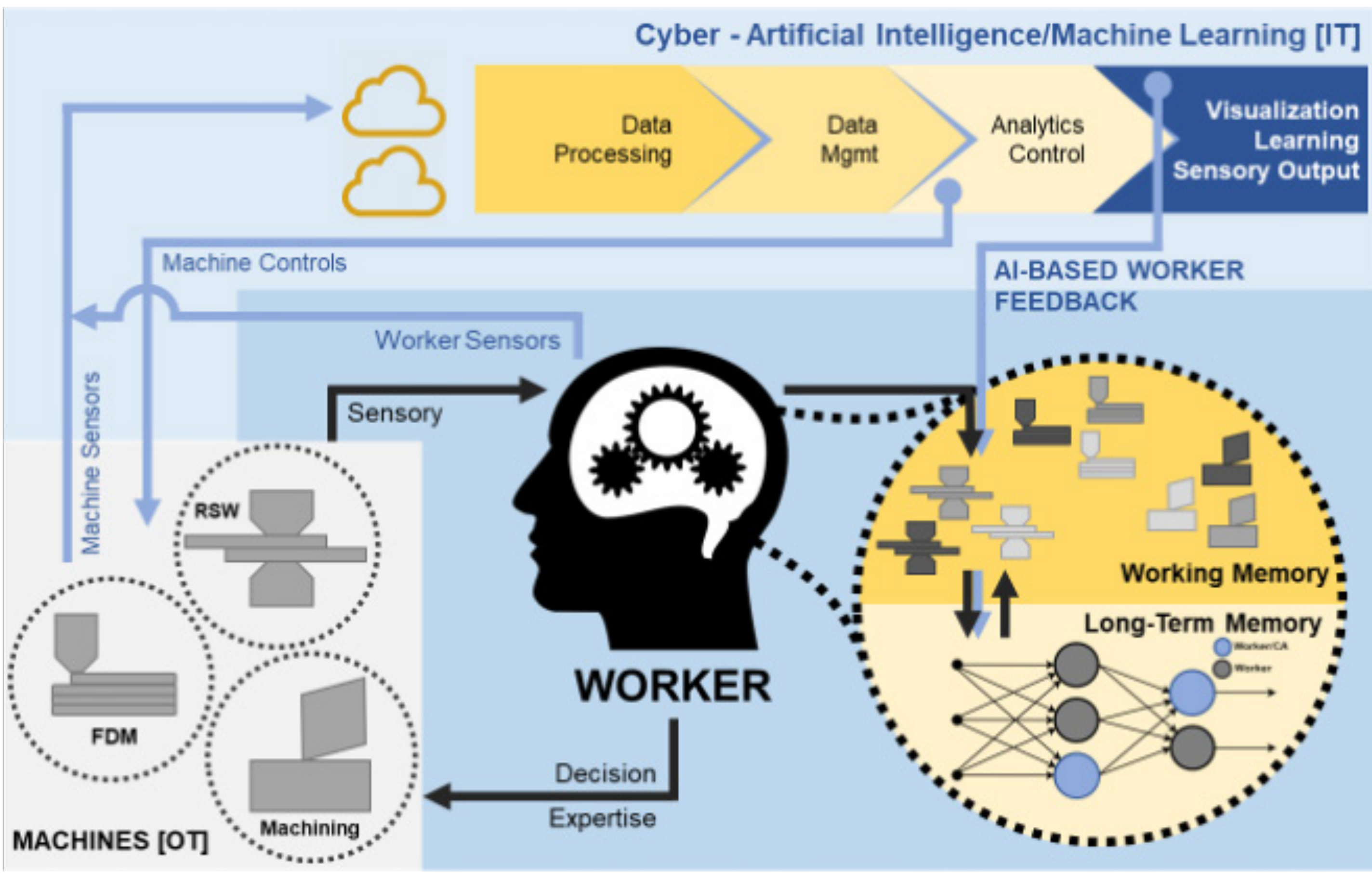

Figure 1. Human manufacturing worker incorporated into the smart manufacturing and ICPS technology loop.

Next generation workforces in ICPS look towards integrating Artificial Intelligence (AI), machine learning, real-time feedback, and biometric worker sensors in order to enhance worker safety, worker mental load, productivity, and manufacturing capability. This paradigm is also illustrated in Figure 1, by expanding the scope to include all aspects of the cyber technologies (or layer), worker sensors – indicated as the blue arrow emitted from the worker, and the smart (AI based) worker feedback providing assistance to workers – indicated as the blue arrow from the visualization/learning/sensory output to the worker working and long-term memory. In this next generation ICPS, machine and worker biometric sensor data is collected, stored, and monitored. Artificial intelligence and machine learning executed in the analytics control step continuously learn from machine and manufacturing worker task execution to provide insights to the worker and control to machine to improve operations. Cyber technologies and the manufacturing worker are linked by augmented reality technologies such as projected visualizations (e.g. LightGuide Systems, LLC) and augmented reality glasses (e.g. Microsoft Hololens) that modify worker perceptions during work. Visualization design and sensory feedback selection are critical to conveying value-added information to the manufacturing worker, and not overwhelming the worker with unnecessary information or graphics.

An important aspect of the digital workforce model in Figure 1 is that machine sensor data and worker sensor data (after filtered through data processing and management stages, passing through the analytics control step, and being delivered to the worker via augmented reality) ultimately influences manufacturing worker working and long-term memory. The direct impact of influencing worker memory (knowledge) is accelerated worker training (through customized feedback based on worker performance) and capturing expert worker knowledge.

Properly equipping workers within the ICPS human technology loop in Figure 1 necessitates a fundamental look into how sensor data and information move through the digital workforce. Figure 2 represents a starting point for this deep dive, which aims to give a clearer view of how the manufacturing worker receives sensory feedback, is being monitored by biometric sensors, and delivers their expertise to enhance machine performance and product quality.

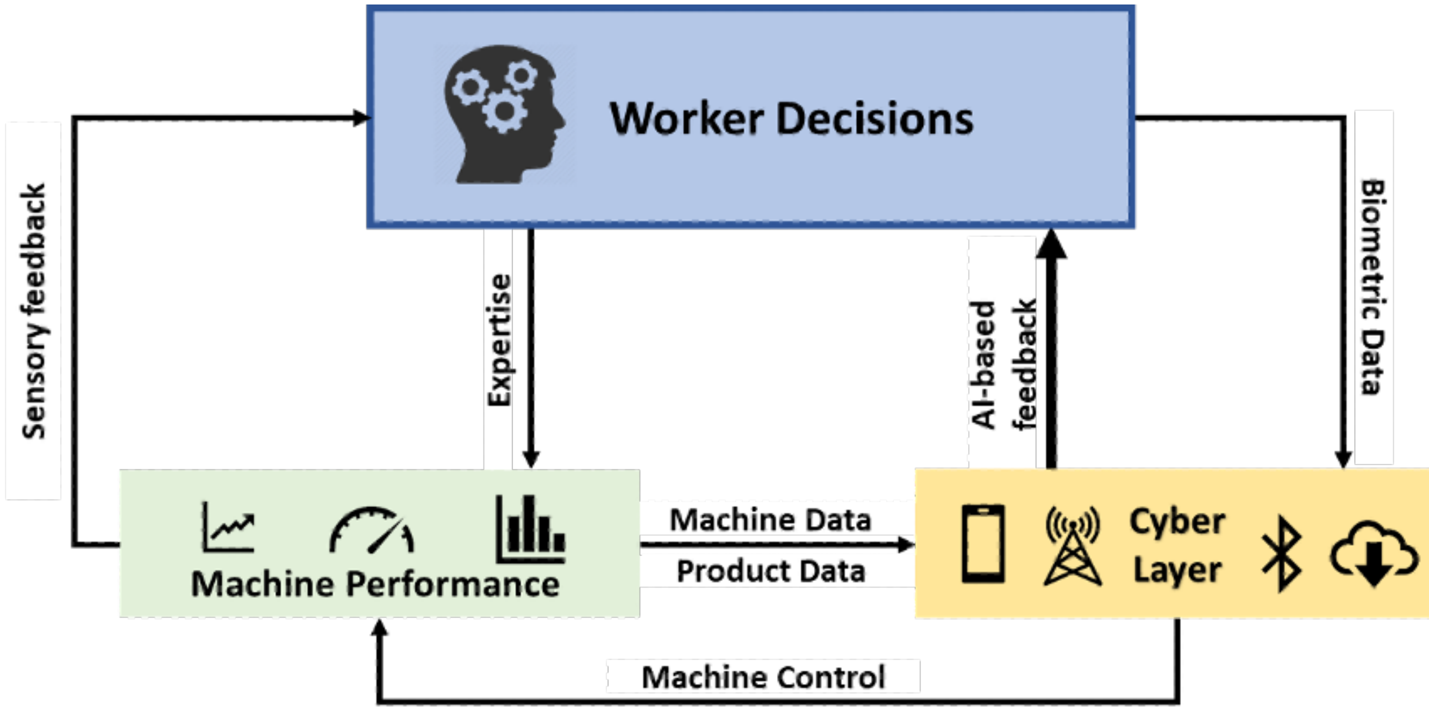

Figure 2: Modeling the flow of sensor data and information that eqips workers with advanced insights in ICPS.

The most straightforward feedback loop in Figure 2 is the worker decision, which influences machine performance through worker expertise. Observations on worker expertise and machine performance are made through worker sensory feedback (e.g. visual, audio, etc.). Machine data and product data are used for direct machine parameter control and by workers to make real-time decisions. Typically, manufacturing machine or product data is communicated to workers through human machine interfaces (HMI) or control charts, eventually influencing worker decisions which then become a function of both worker sensory feedback and machine data monitoring. The cyber layer leverages machine learning and artificial intelligence to extract unseen insights from machine and product data, and to mitigate data overload to the worker. This is accomplished by intelligently processing incoming machine, product, and biometric sensor data streams, to provide AI-based feedback that complements worker sensory feedback, and accelerates worker learning, expertise, and decision making. Advanced monitoring capabilities also extend to the worker, illustrated by the cyber layer integrating worker biometric sensor data to monitor worker response to AI-based feedback delivered by augmented reality technologies or displays.

The AI-based worker feedback, Figure 2, is the critical link in this loop because it closes the gap between the worker, machine, and cyber layer. The amount of information delivered to the worker and the effectiveness of technologies (e.g. projectors or augmented reality glasses) to communicate feedback to the worker is a significant unanswered question for the digital workforce in the future.

Challenges & Opportunities

Fully integrating the human factor into equipping the next generation digital workforce is a difficult task given the complex interaction between multiple complex systems (i.e., manufacturing machine, manufacturing worker decision making, and artificial intelligence and machine learning models). However, success is predicted to add such value to manufacturing operations that a significant competitive advantage is achieved. Critical challenges that exist within this thrust include, but are not limited to:

1. Validating visualization technologies and approaches that effectively communicate insight derived from artificial intelligence and machine learning models to the worker. This is required in order to ensure that AI-based feedback enhances the digital workforce without detracting from worker tasks. An example is designing augmented reality (AR glass) visual feedback cues that improve worker actions or learning rather than distracting from the task at hand.
2. Broadening the acceptance of augmented reality and XR (extended reality) technologies among manufacturing workers at multiple levels (e.g., operators, manufacturing engineering, maintenance engineers, etc.).
3. Optimizing AI-based feedback for individual worker needs and expertise levels. Automating and adapting worker feedback needs using biometric sensor data and artificial intelligence methods has the potential to remove variability across worker performance and accelerate worker training.
4. Expanding the current library of case studies that demonstrate the factory level benefits of equipping a digital workforce through the return on investment of ICPS, augmented reality technologies, and AI-based methods.
5. Keeping pace with advancements in augmented reality technologies, artificial intelligence, machine learning methods, and industrial internet of things systems to ensure the digital workforce is operating at the cutting edge of manufacturing technologies.

Investing in the human factor of the digital workforce has shown to be an opportunity for manufacturing companies to be successful. McKinsey and the World Economic Forum's Global Lighthouse Network determined that manufacturing leaders in this network not only implemented smart technologies but also made critical investments in their people (Ellingrud et al., 2020). Successful companies were also shown to deliver training that fits the specific needs of individuals in their organizations, which is an aspect the system described Figures 1 and 2 aims enhance based on biometric sensor data and artificial intelligence, and deliver in real-time, during task completion.

Case Study

Wayne State University teams are tackling these challenges at Wayne State's Smart Manufacturing Demonstration Center (SMDC), Figure 3. The SMDC was initiated in late 2017 through a partnership with Cisco Systems' State Digital Acceleration (SDA) initiative. Michigan was the first state to join Cisco's program, which aims to advance the digital manufacturing agenda, bolster financial growth, attract new investment, and increase innovation potential. The 25,000-square-feet high bay area of the Wayne State's College of Engineering Manufacturing Engineering Building is home to the SMDC. The SMDC contains three cells that demonstrate smart manufacturing and ICPS principles on a variety of manufacturing equipment and for multiple manufacturing scenarios. The SMDC acts as a hub focused on developing the next generation of digital manufacturing professionals and leaders in automation and robotics. It houses a variety of equipment and software, connected with Cisco's secured systems infrastructure, that enables research and education on processes and machines such as collaborative robots, additive manufacturing, computed tomography (CT) scanning, automated laser line scanning, and resistance spot welding. SMDC capabilities also enable researchers to explore aspects of the ICPS, Internet of Things (IoT), and Industry 4.0 (e.g., manufacturing data management, storage, infrastructure, and security).

Figure 3: The Smart Manufacturing Demonstration Center (SMDC) located in the Manufacturing Engineering Building at Wayne State University, Detroit, Michigan

The digital workforce and manufacturing workers in the ICPS technology loop are specific thrust areas that the SMDC is addressing. Currently, researchers at Wayne State are advancing circular economy disassembly systems by studying the application of collaborative robotics in disassembly operations. This research has applications to automotive remanufacturing and recycling networks, and to scaling up critical material (e.g. neodymium magnets for next generation energy technologies) recovery in order to secure a reliable critical material supply base in the face of international competition. Two specific collaborative robotic disassembly case studies are being pursued at the SMDC; 1) Evaluating manufacturing worker engagement during collaborative robotic assisted disassembly and 2) Rapid reprogramming high volume disassembly systems based on information extracted from worker-collaborative robotic disassembly.

Case 1. Manufacturing worker engagement during collaborative robotic disassembly

Since worker and collaborative robot interaction is the critical aspect of collaborative automation, it is essential that worker intent and engagement be monitored along with collaborative robot position, productivity, and task completion. Worker engagement is defined in this case study as the worker's level of focus (conversely, worker distraction) on a given task or set of tasks (Figure 4). Artificial intelligence and machine learning models are very powerful in a collaborative robot-worker station, as they can monitor and predict how engaged, or symbiotic, a worker is with an associated collaborative robot. Worker engagement data provides a quantitative assessment of where worker focus is directed during a task, while collaborative robot positional sensors, machine code, and action execution provide data on how well a task was performed. For this study, an engagement prediction technology developed by the CNU Artificial Intelligence Convergence Research Institute is employed.

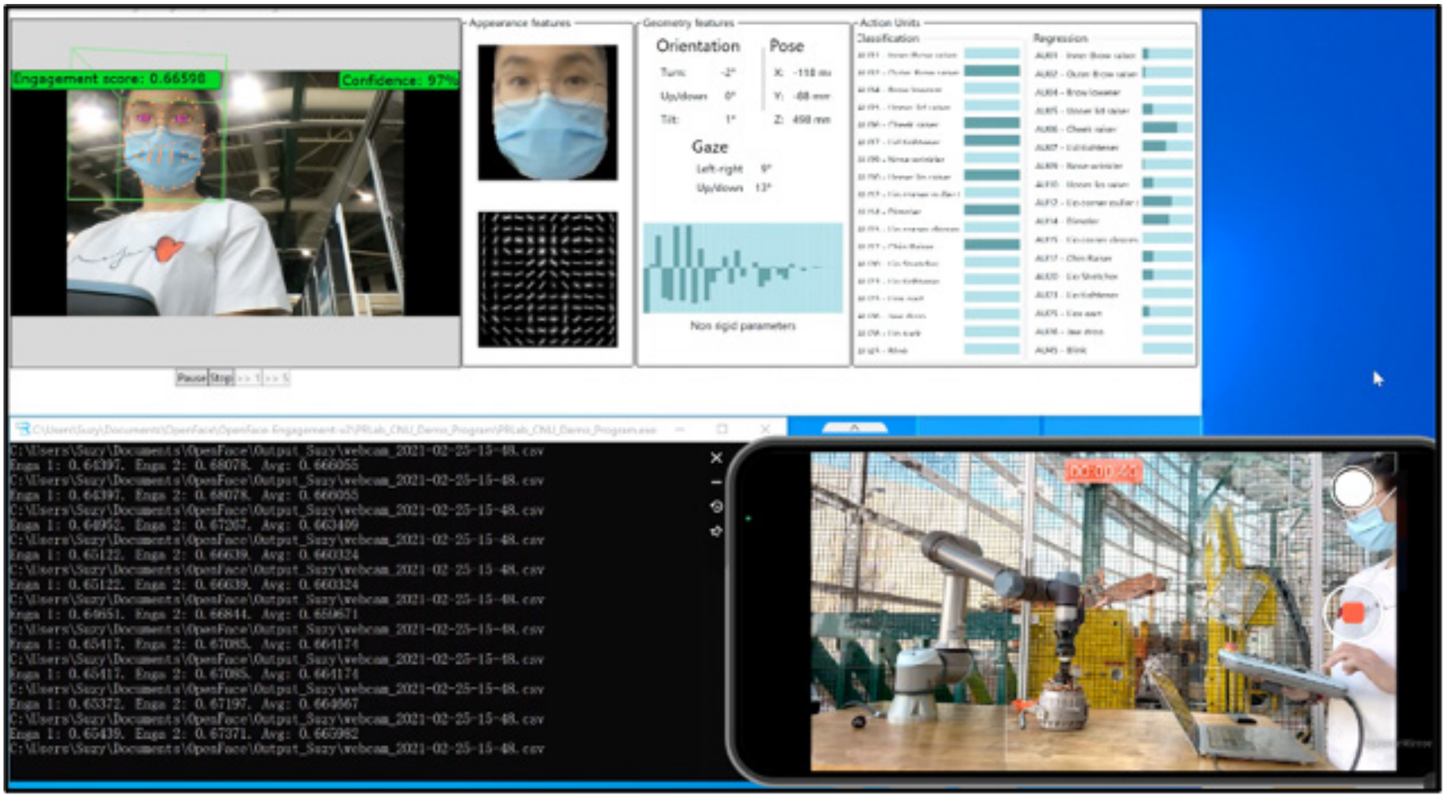

Figure 4: Measuring worker engagement by recognizing facial features during collaborative robotic (bottom right corner)

Wayne State's SMDC is studying manufacturing worker engagement while undertaking disassembly activities, Figure 4. A variety of disassembly operations, such as the rotational movement for screw removal and vector movements to remove component housings, are executed based on a pre-determined set of disassembly instructions. Data collected is intended to evaluate Future Manufacturing job skills (Ellingrud et al., 2020; Luce, 2019; Gray, 2016) such as visualization, programming, and user experience of the collaborative robotic disassembly station design. Once pre-determined disassembly instructions are complete, disassembly tasks and requirements are varied in order to evaluate worker cognitive flexibility, visualization, and equipment maintenance, repair, and control. Interpretation of worker engagement data and collaborative robot programming and position data gives insights into if the disassembly task is executed correctly or if the worker adapted the collaborative robot sufficiently to compensate for a new disassembly operation.

Case 2. Collaborative robotic rapid reprogramming of high volume disassembly system

This case study places the manufacturing worker at the beginning of a digital process to learn disassembly operations from a collaborative robot-human station and disseminate to stations within a high-volume disassembly system. High-volume disassembly requires achieving a high level of automation that is difficult due to the variety of product types and designs that are acquired for disassembly. This case study has two main components,

illustrated in Figure 5 (Prioli and Rickli, 2020). First, is a learning and training station composed of a collaborative robot and human worker that captures the disassembly operations of a new, incoming end-of-use product (bottom left of Figure 5). Disassembly learning and training require the knowledge of the worker and the tracking of the collaborative robot to learn operations required to disassembly the product and distribute it to a cloud-based data management system. Second, disassembly planning methods retrieve disassembly information stored in the cloud and disseminate it to the preferred disassembly stations or automated guided vehicles (AGVs).

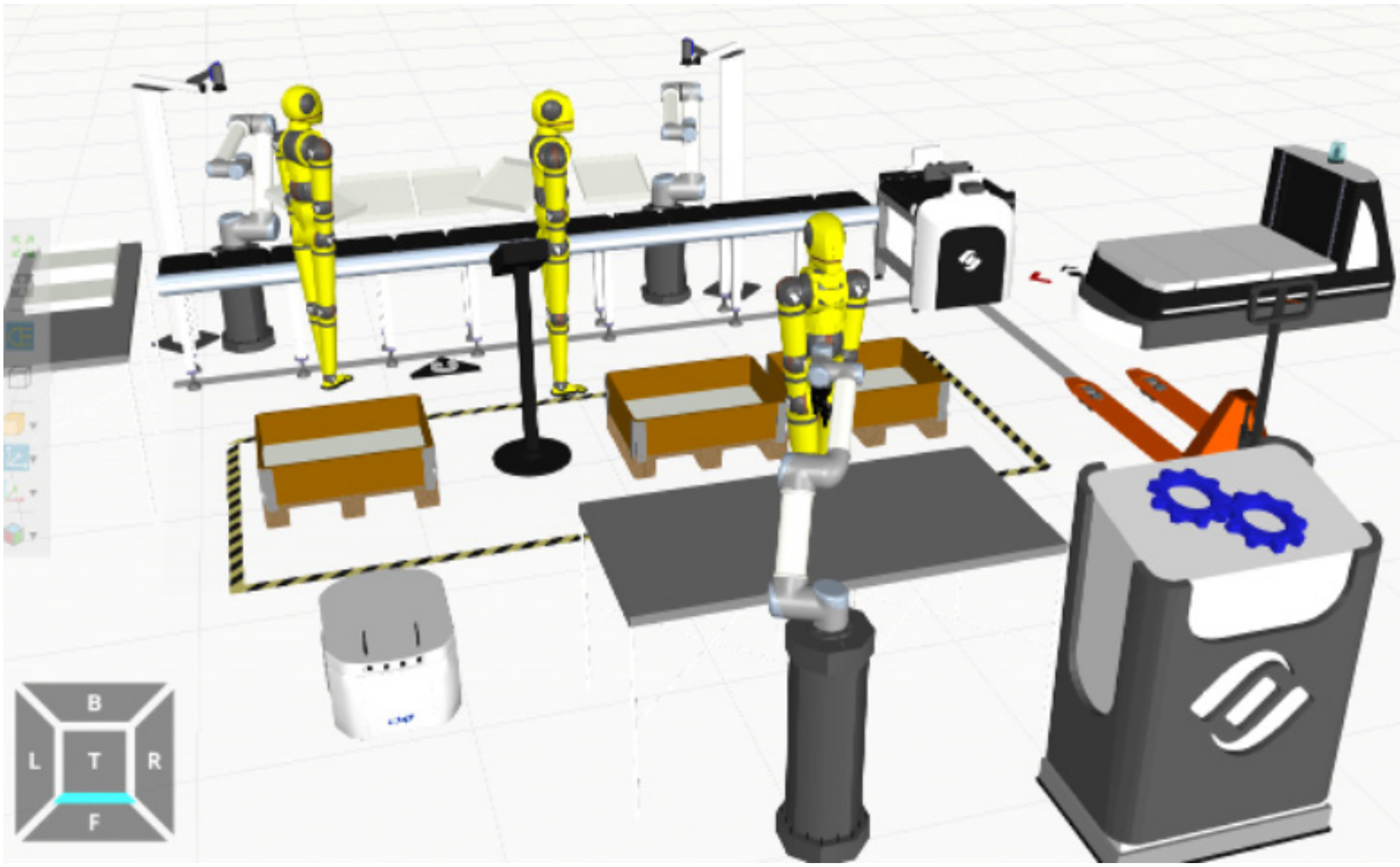

Figure 5. High volume disassembly system composed of AGVs, collaborative robots, and traditional 6 degrees of freedom robots all reprogrammed based on information learned from robotic disassembly (separate station in the bottom left.)

The manufacturing worker is responsible for manipulating the collaborative robot to direct the product disassembly learning process. Disassembly data is then merged, encoded into the digital industrial network protocol, and stored in a retrievable database. Once disassembly information is developed and managed, it is the responsibility of enterprise systems to compute optimal machine schedules and deliver required disassembly operation information, such as fastener coordinates, fastener type, and disassembly direction, from network data storage to individual stations at the right time, depending on the current disassembly demands and jobs.

Wayne State has constructed a disassembly learning and training testbed and developed methods to translate collaborative robotic trajectory programs into disassembly information blocks that can be delivered to stations in high volume disassembly systems. To capture worker input, the worker creates placeholders or marks during collaborative robot manipulation. The marks are assigned as worker variables in the collaborative robot program. Worker variables identify disassembly tools, disassembled components, and the complete of a set of disassembly operations, while collaborative robot position and program variables capture component locations and disassembly directions. Overall, integrating industrial automation with the manufacturing worker through collaborative robotics and information systems had provided unique capabilities to capture disassembly information at a rapid pace.

Action Items

- Pursue public-private partnerships via industry and academic collaboration to adapt ICPS tools to enhance expertise, flexibility, and adaptability of manufacturing workers.
- Invest in new training and education systems that are specific to individual worker needs, and promote knowledge transfer across manufacturing workers.
- Promote synergistic technology (connecting IT and OT aspects) training and education to better prepare workers to shift skill sets to IT/OT based skills.
- Lay the groundwork for implementing biometric worker sensors that capture worker safety, worker mental load, and manufacturing capability.
- Develop visualization mechanisms for AR and XR technologies to optimally display value-added AI-based analytics results. This requires a balance between information delivered and worker information overload.
- Design symbiotic and AR enabled working environments in early manufacturing process, station, and line design phases.

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